



http://xkcd.com/894/

Neural Networks

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CS51A
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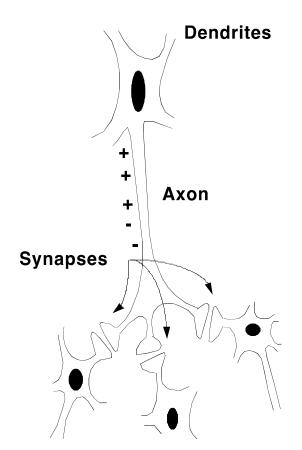
Neural Networks

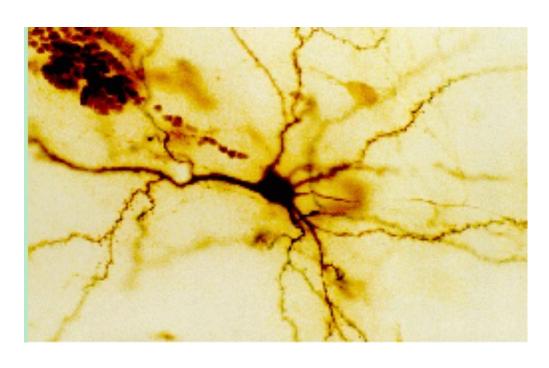
Neural Networks try to mimic the structure and function of our nervous system

People like biologically motivated approaches



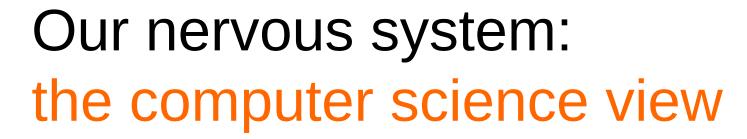
Our Nervous System

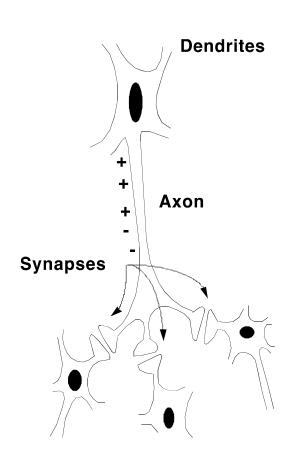




Neuron

What do you know?





the human brain is a large collection of interconnected neurons

a **NEURON** is a brain cell

- they collect, process, and disseminate electrical signals
- □ they are connected via synapses
- they FIRE depending on the conditions of the neighboring neurons





The human brain

- \square contains $\sim 10^{11}$ (100 billion) neurons
- □ each neuron is connected to ~10⁴ (10,000) other neurons
- □ Neurons can fire as fast as 10⁻³ seconds

How does this compare to a computer?



Man vs. Machine



10¹¹ neurons 10¹¹ neurons 10¹⁴ synapses 10⁻³ "cycle" time



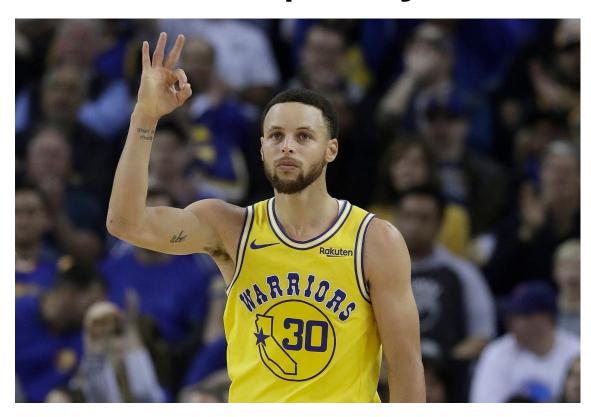
10¹⁰ transistors

10¹¹ bits of ram/memory

10¹³ bits on disk

10⁻⁹ cycle time

Brains are still pretty fast



Who is this?





If you follow basketball, you'd be able to identify this person in under a second!

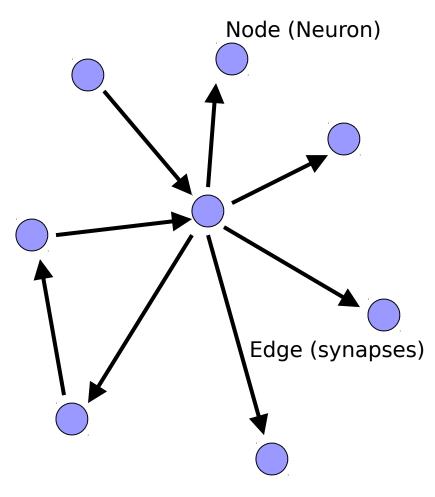
Given a neuron firing time of 10⁻³ s, how many neurons in sequence could fire in this time?

☐ A few hundred, maybe a thousand

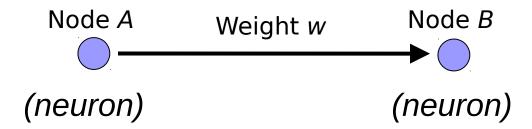
What are possible explanations?

- either neurons are performing some very complicated computations
- brain is taking advantage of the massive parallelization (remember, neurons are connected ~10,000 other neurons)

Artificial Neural Networks



our approximation

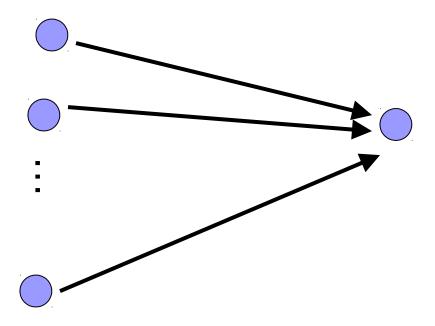


W is the strength of signal sent between A and B.

If A fires and w is **positive**, then A **stimulates** B.

If A fires and w is **negative**, then A **inhibits** B.



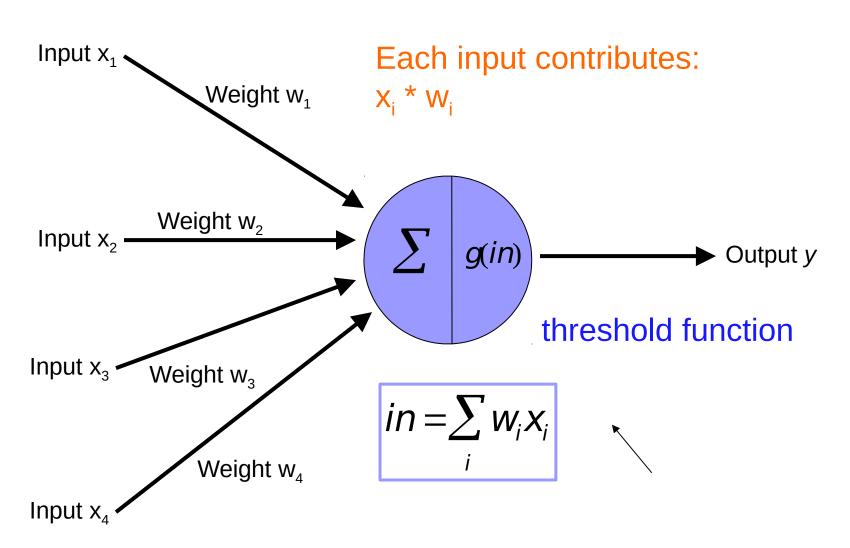


A given neuron has many, many connecting, input neurons

If a neuron is stimulated enough, then it also fires

How much stimulation is required is determined by its threshold







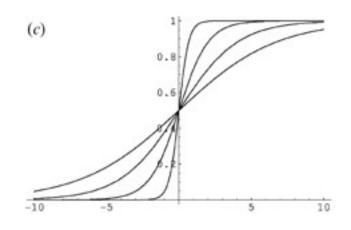
Possible threshold functions

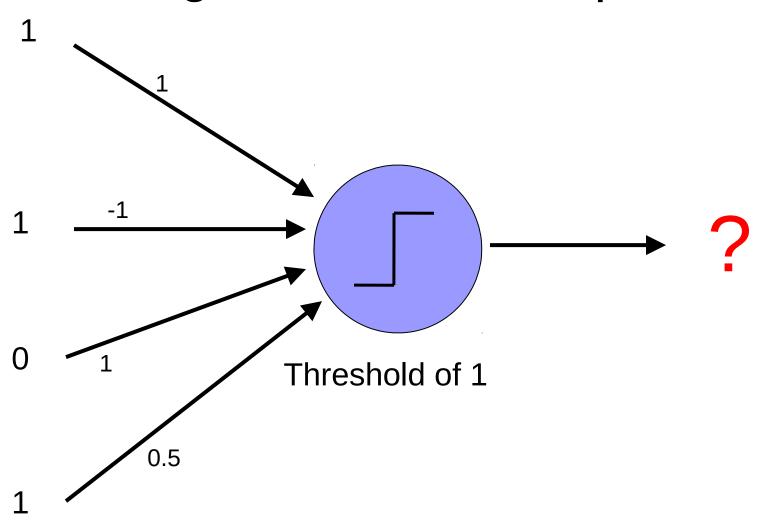
hard threshold

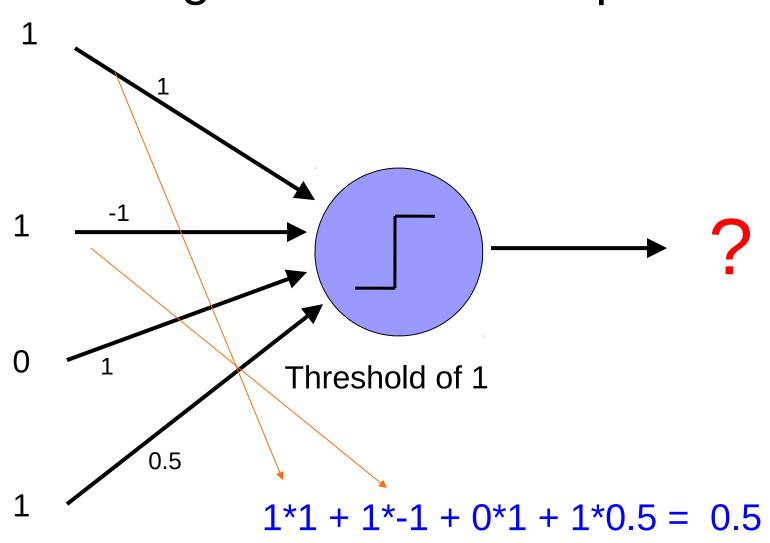
$$g(x) = \begin{cases} 1 & \text{if } x \ge \text{threshold} \\ 0 & \text{otherwise} \end{cases}$$

sigmoid

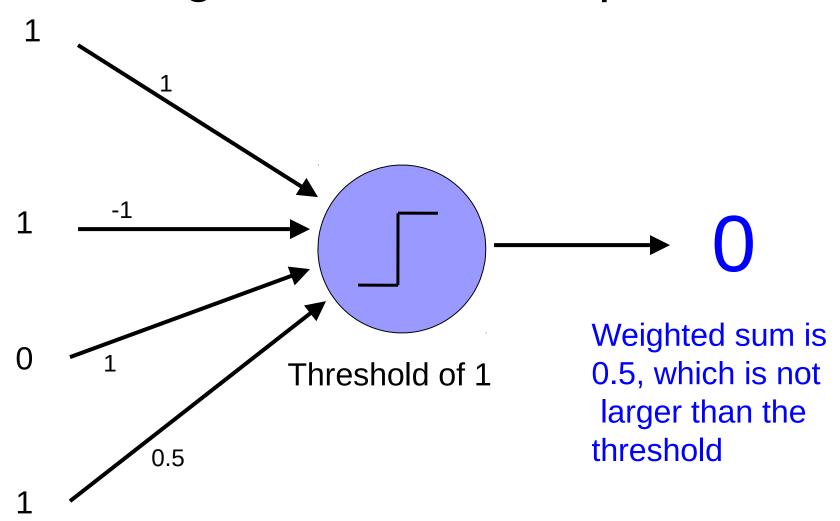
$$g(x) = \frac{1}{1 + e^{-ax}}$$



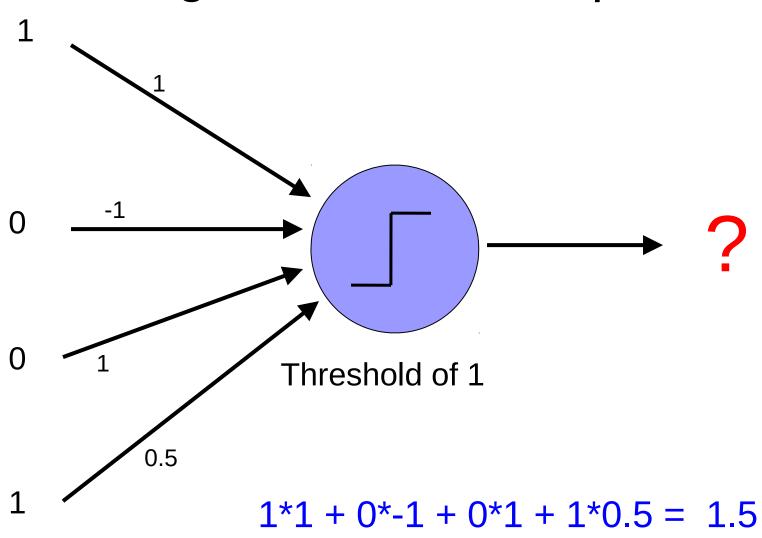




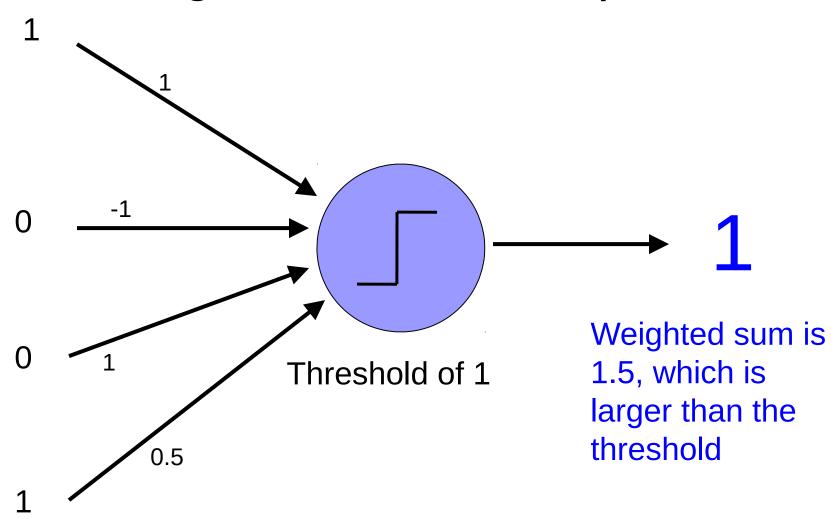
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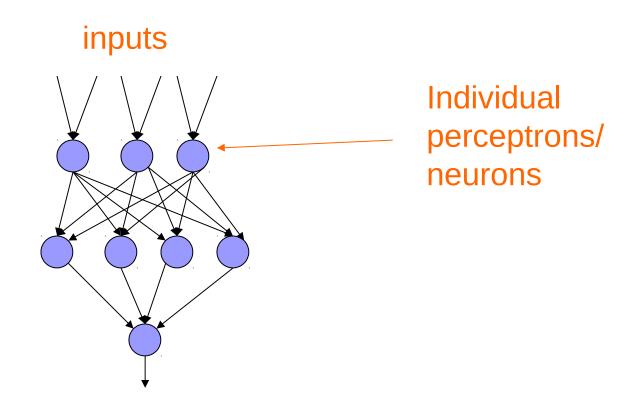
м



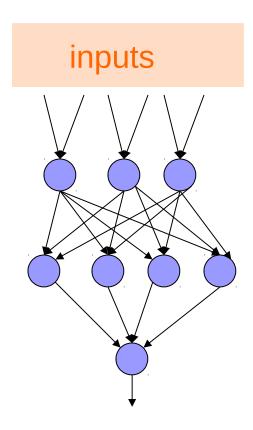
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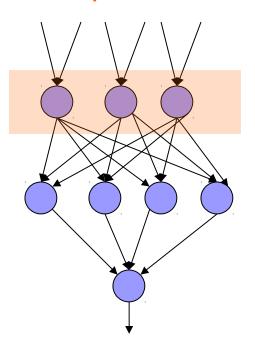




some inputs are provided/entered



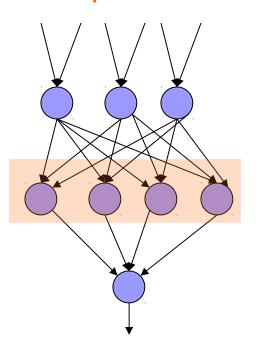
inputs



each perceptron computes and calculates an answer



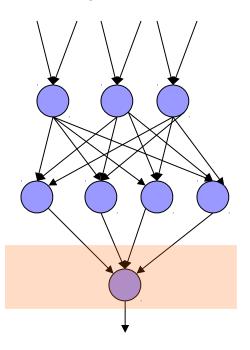
inputs



those answers become inputs for the next level



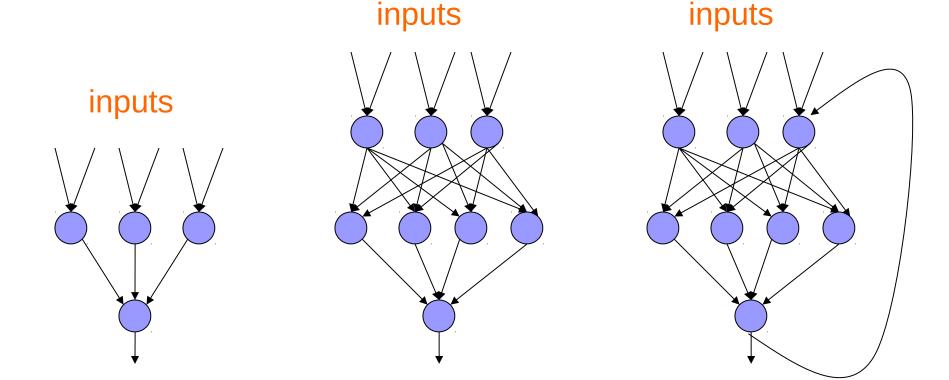
inputs



finally get the answer after all levels compute

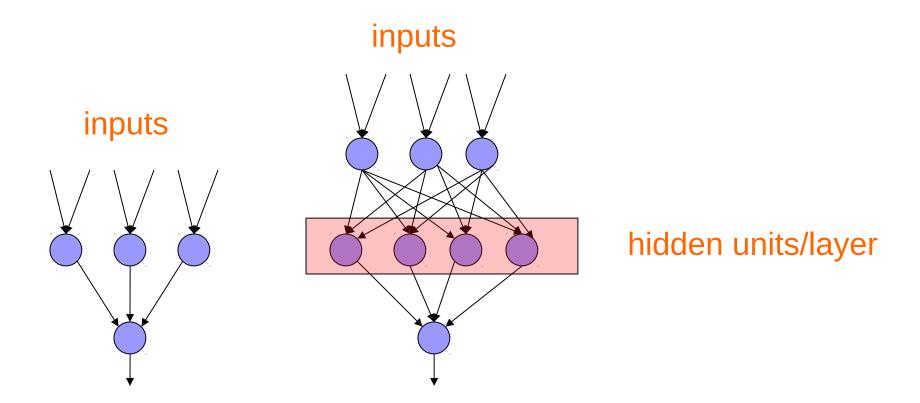


Different kinds/characteristics of networks



How are these different?

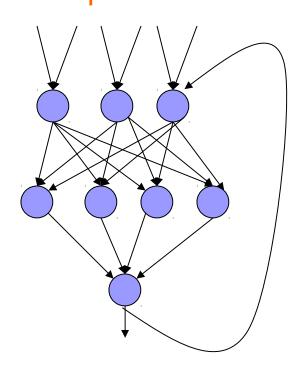




Feed forward networks



inputs



Recurrent network

Output is fed back to input

Can support memory!

How?

v

History of Neural Networks

McCulloch and Pitts (1943) – introduced model of artificial neurons and suggested they could learn

Hebb (1949) – Simple updating rule for learning

Rosenblatt (1962) - the perceptron model

Minsky and Papert (1969) – wrote *Perceptrons*

Bryson and Ho (1969, but largely ignored until 1980s--Rosenblatt) – invented back-propagation learning for multilayer networks



Training the perceptron

First wave in neural networks in the 1960's

Single neuron

Trainable: its threshold and input weights can be modified

If the neuron doesn't give the desired output, then it has made a mistake

Input weights and threshold can be changed according to a learning algorithm

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Examples - Logical operators

AND – if all inputs are 1, return 1, otherwise return 0

OR – if at least one input is 1, return 1, otherwise return 0

NOT – return the opposite of the input

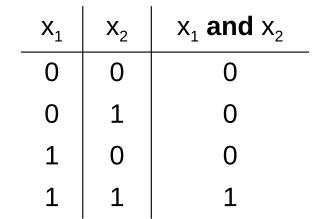
XOR – if exactly one input is 1, then return 1, otherwise return 0

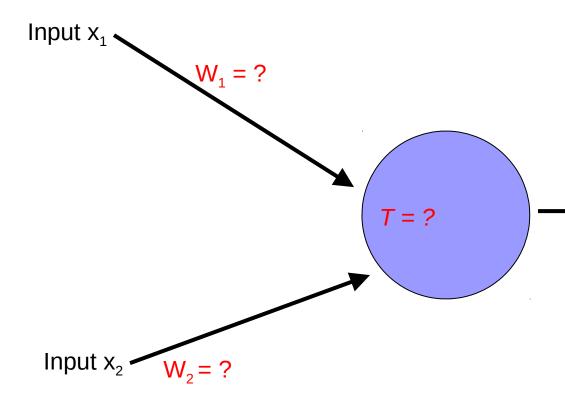
AND

X_1	X ₂	X_1 and X_2
0	0	0
0	1	0
1	0	0
1	1	1



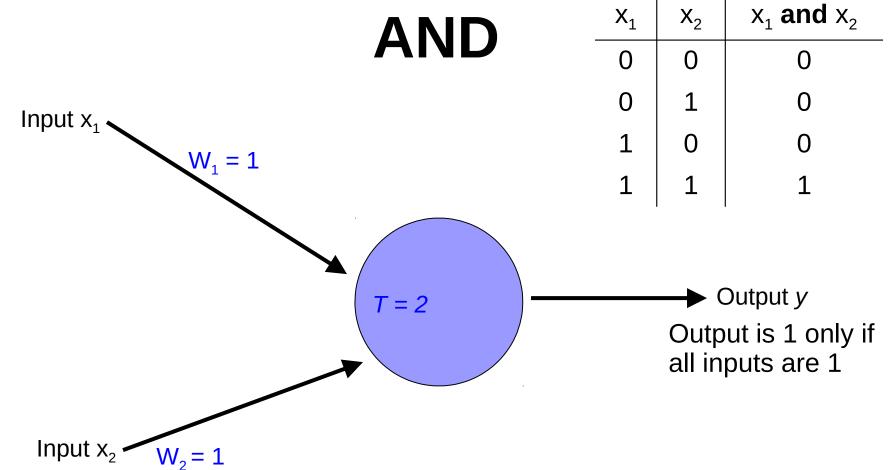
AND





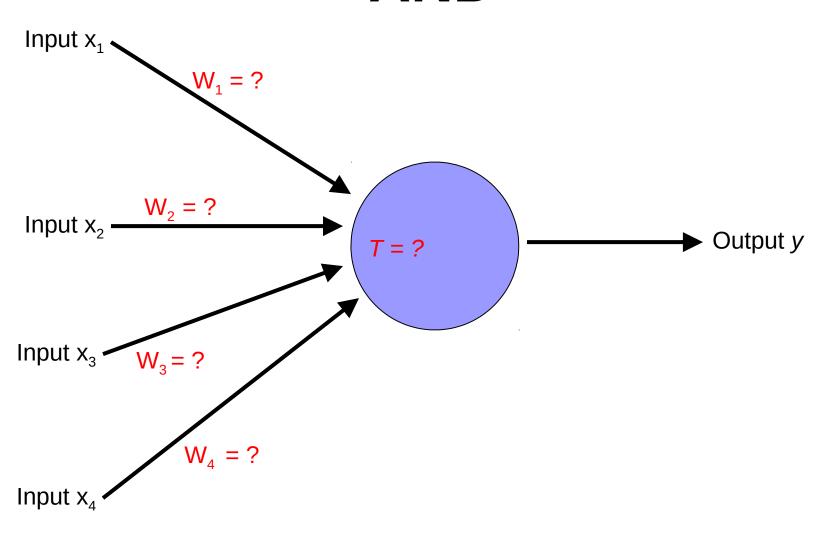
Output *y*





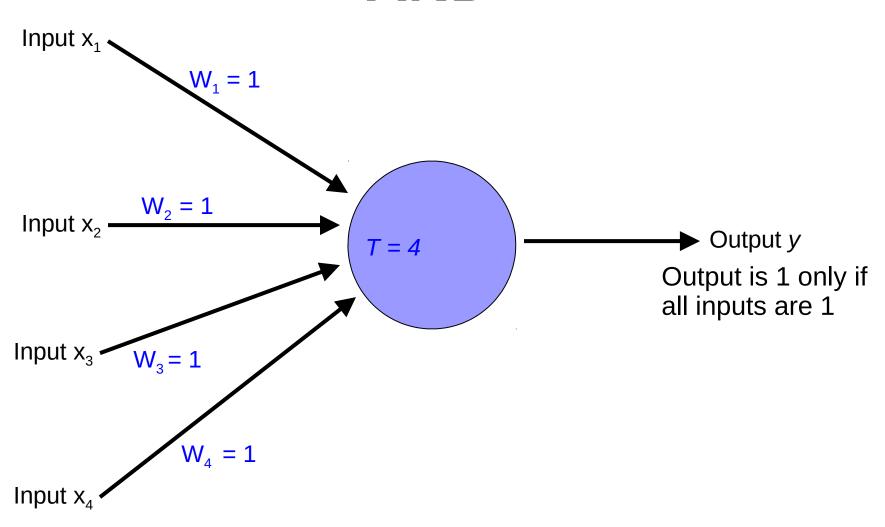
Inputs are either 0 or 1

AND





AND



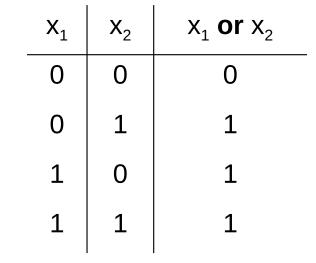
Inputs are either 0 or 1

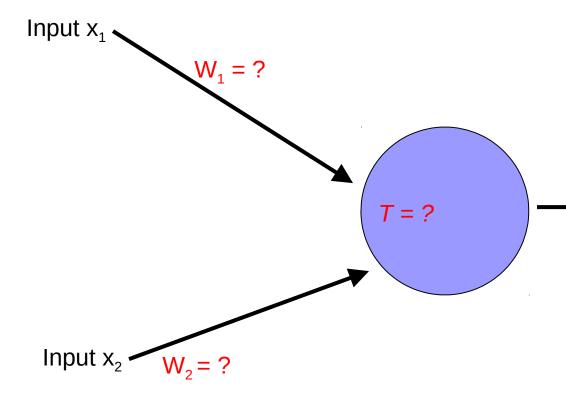
OR

X_1	X ₂	X_1 or X_2
0	0	0
0	1	1
1	0	1
1	1	1



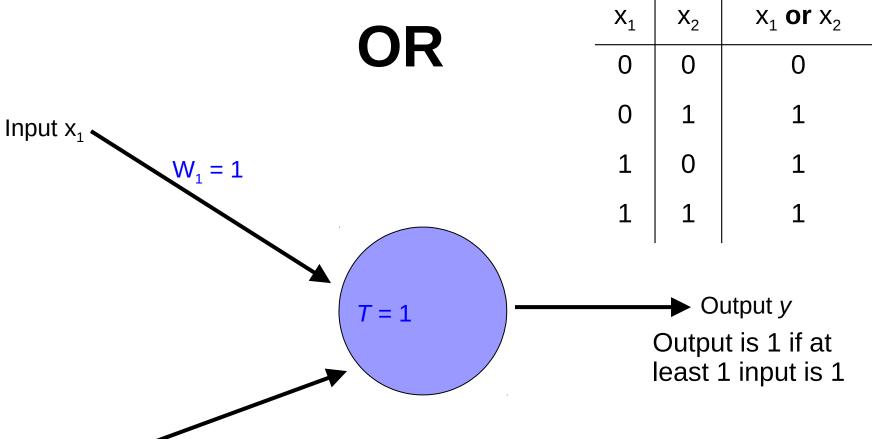






► Output *y*





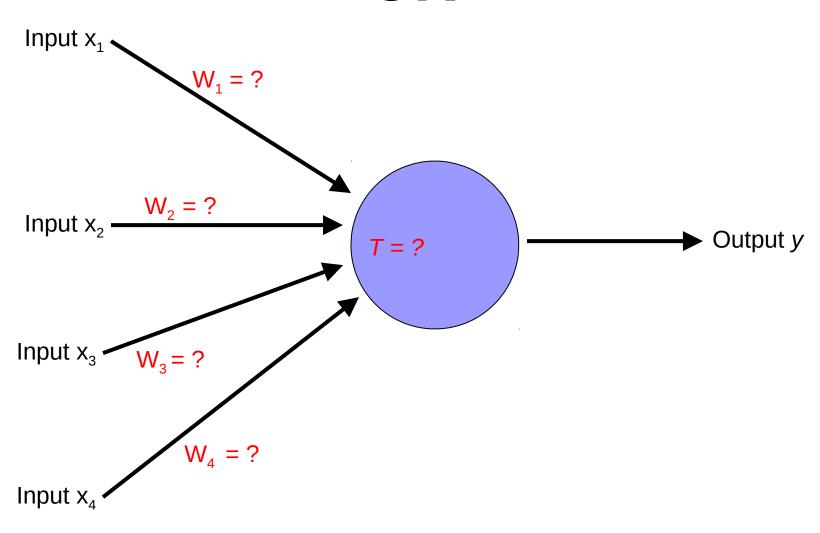
Inputs are either 0 or 1

Input x₂

 $W_2 = 1$

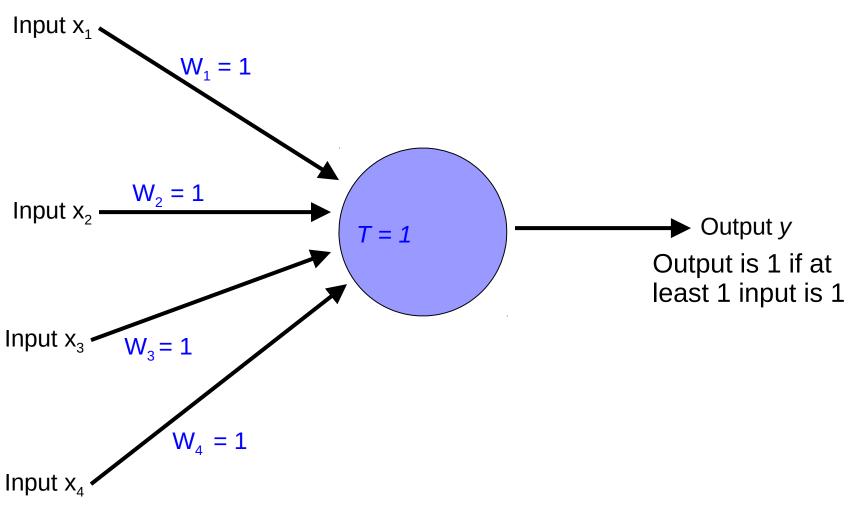


OR





OR



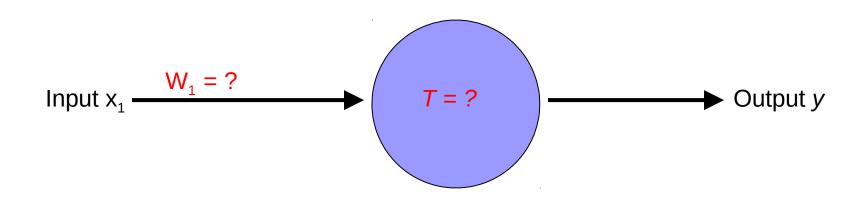
Inputs are either 0 or 1

NOT

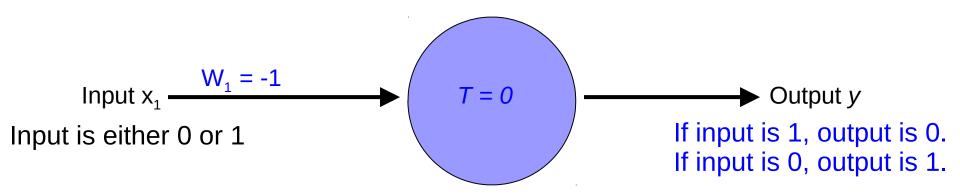
X_1	not X ₁
0	1
1	0

NOT

X_1	$\mathbf{not} \ \mathbf{x}_{_{1}}$
0	1
1	0

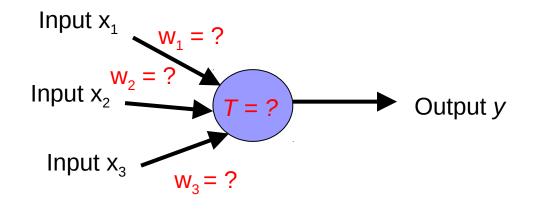


NOT

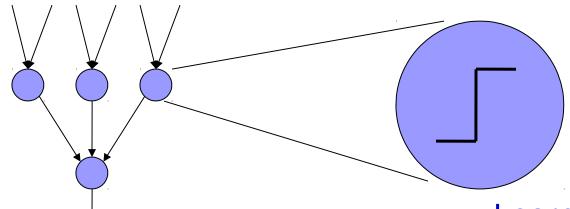




X ₁	X ₂	X ₃	X_1 op X_2
0	0	0	1
0	1	0	0
1	0	0	1
1	1	0	0
0	0	1	1
0	1	1	1
1	0	1	1
1	1	1	0

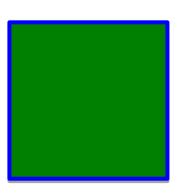


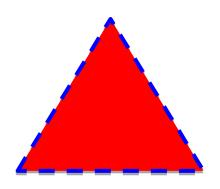
Training neural networks

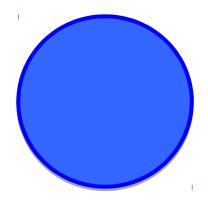


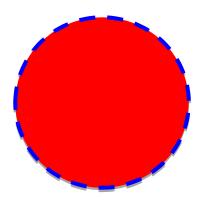
Learn the individual weights between nodes

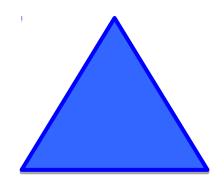
Learn individual node parameters (e.g. threshold)



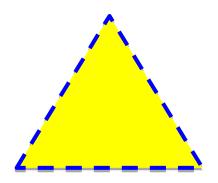


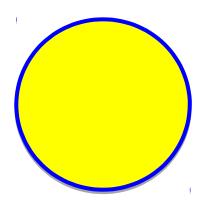


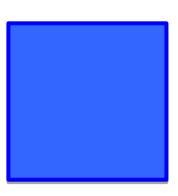












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A method to the madness

blue = positive

yellow triangles = positive

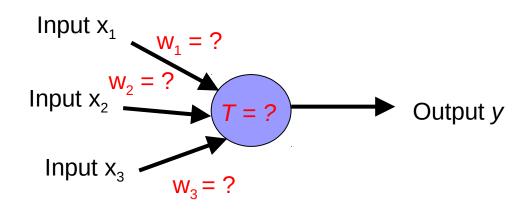
all others negative

How did you figure this out (or some of it)?

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Training neural networks

X ₁	X ₂	X ₃	x ₁ and x ₂
0	0	0	1
0	1	0	0
1	0	0	1
1	1	0	0
0	0	1	1
0	1	1	1
1	0	1	1
1	1	1	0
		l	l



- 1. start with some initial weights and thresholds
- 2. show examples repeatedly to NN
- 3. update weights/thresholds by comparing NN output to actual output